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Summary

The production of goods and services generates greenhouse gases (GHGs) and air pollution both directly and through the activities of the supply chains on which they depend. The analysis of the latter—called embodied emissions—in the cause of internationally traded goods and services is the subject of this paper. We find that trade openness increases embodied emissions in international trade (EET). We also examine the impact of sector trade on EET. By applying a fixed-effect model using large balanced panel data from 187 countries between 1990 and 2011, we determine that each unit of increase in trade openness results in a 10% to 23% increase in GHG embodied emissions (EE). The sector trade effect is also significant for the EE of carbon dioxide (CO_2), methane (CH_4) nitrous oxide (N_2O), carbon monoxide (CO), non-methane volatile organic compounds (NMVOCs), particulates (PM_{10}) and sulfur dioxide (SO_2). Our findings also clearly indicate that the impact of the GDP on the EE of exports is positive, increasing emissions, but that it is negative on the EE of imports. We suggest that countries monitor trade sector emissions and trade openness to mitigate global embodied GHG emissions and air pollutants.

Keywords: environmental economics, greenhouse gases (GHGs), industrial ecology , input-output analysis, international trade, trade and environment

Introduction

International trade is increasing continuously and the globalized economy has impacts on environmental quality. Emissions occur either directly through the production processes or indirectly in the global supply chain. The accumulated emissions emitted in the production of the product are said to be embodied emissions (EE) (Peters and Hertwich 2008).

The effect of trade on the environment, however, can be positive or negative. Therefore, it is important to accurately determine the environmental impacts resulting from pollution embodied in trade (Peters and Hertwich 2006). The purpose of this research is to investigate the causes of global EE by examining trade openness, trade by sector, and gross domestic product (GDP) data.

Existing empirical studies find conflicting evidence about the impact of trade on the environment (Koo 1974; Walter 1976; Leonard 1988; Tobey 1990; Dean 1992; Low and Safadi 1992; Gale IV 1995; Jayadevappa 1996). Some studies indicate that lower growth rates in pollution intensity and open trade policies are positively correlated (Birdsall and Wheeler 1993; Lucas et al. 1992; Wheeler and Martin 1992). However, other researchers such as Rock (1996) have argued that open trade policies create more pollution. To address these concerns, the relationship between trade and embodied emissions (EE) must be understood.

The environmental pollution associated with consumption in one country is shifted to another country through trade (Yunfeng and Laike 2010). Accordingly, open trade often improves the environments of developed countries while exacerbating the damages to the environments of developing countries (Copeland and Taylor 1994, 1995). More specifically, as greenhouse gases (GHG) are the primary contributors to global warming, our research aims to determine whether trade leads to increased levels of GHG emissions. This is a logical hypothesis given that international trade exert tremendous impacts on carbon emissions in economies (Peters and Hertwich 2008; Peters et al. 2011).

Trade Openness impact on the Environment

The more open an economy the greater the impact of foreign trade on a country's environmental figures (Machado et al. 2001). The environmental effects of trade openness is a critical question with respect to economic policy (Copeland and Taylor 2013; Taylor 2004), and thus the correlation between trade openness and environmental quality has attracted considerable interest (Antweiler et al. 1998; Cole and Elliott 2003; Frankel and Rose 2005; Harbaugh et al. 2002). Antweiler et al. (1998) estimates the effects of trade openness and the GDP on environmental pollution by using data for sulfur dioxide (SO_2) intensity and finds that SO_2 concentrations increase when the GDP increases and decreases as trade openness decreases.

Global trade expands at a rate that is faster than economic growth, driven by the development of transport technologies. This leads to the risk that growth in international trade may hide environmental damage as it separates consumption from production (Hertwich 2012; Lenzen et al. 2012b). Moreover, increased trade openness correlates to increased pollution (Managi et al. 2009), which has environmental consequences as exports and imports either increase or decrease local production and consequently greenhouse gas (GHG) emissions (Amor et al. 2011).

Embodied Emissions by Industry Sector

The impact of exports and imports on global EE differ according to the specific industries involved. Some industries are significantly increasing their embodied emission in exports (EEE) when other industries are impacting embodied emissions through imports (EEI). As we did not find any literature that had studied the impact of trade openness on EET on a global scale, we address this issue in our empirical work.

Input-Output Analysis for the Analysis of Embodied Emissions

Economic-environment models based on input–output analysis are able to capture indirect environmental impacts caused by production. This makes them suitable for the estimation of EE. In the last few years the use of sophisticated multi-region, multi-sector input–output framework have increased. Improvements in data availability and quality have changed the situation and more sophisticated models have been described (Wiedmann et al. 2007). Input–output tables are available for many developed and some developing countries. Although the sector aggregation varies from country to country, the principal economic accounting framework is a standardized process (United Nations 1999, 2003).

Though there is much literature focused on the impact of trade on emissions by using multi-region input-output (MRIO) data, the scope of industry-specific analysis by using econometric model has been extremely limited. In addition, this method only directly considers the changes in international trade with respect to final consumers by industry and does not incorporate arbitrary variables such as trade openness. Moreover, global level studies have not focused on industry level changes. Thus, our work contributes to the literature as it identifies EE by industry in international trade. The paper is structured as follows: the next section describes the model, and the following section explains the data. We then discuss the results and the final section presents the conclusion and policy implications.

Model

We apply a panel regression model to examine the impact of trade openness and sectors' trade on EEE and EEI. A model for the relationship between EEE and its determinants can be estimated by applying equation 1.

$$
\begin{aligned}
Log\,(EEE_{rt}) = \ & \alpha_0 + \alpha_1\, Trade\ openness_{rt} + \alpha_2\, Log\,(Ex\_Ag_{rt}) \\
& + \alpha_3\, Log\,(Ex\_Mn_{rt}) + \alpha_4\, Log\,(Ex\_Ft_{rt}) + \alpha_5\, Log\,(Ex\_Ot_{rt}) \\
& + \alpha_6\, Log\,(Ex\_Me_{rt}) + \alpha_7\, Log\,(Ex\_Em_{rt}) + \alpha_8\, Log\,(Ex\_Tr_{rt}) \\
& + \alpha_9\, Log\,(Ex\_Om_{rt}) + \alpha_{10}\, Log\,(Ex\_Eg_{rt}) + \alpha_{11}\, Log\,(Ex\_Tt_{rt}) \\
& + \alpha_{12}\, Log\,(Ex\_Bs_{rt}) + \alpha_{13}\, Log\,(Ex\_Os_{rt}) + \alpha_{14}\, Log\,(GDP_{rt}) \\
& + \alpha_{15}\, Population + \delta_t + \mu_{rt} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)
\end{aligned}
$$

The relationship between EEI and its determinants can be estimated by applying equation 2.

$$
\begin{aligned}
Log\,(EEI_{st}) = \ & \beta_0 + \beta_1\, Trade\ openness_{st} + \beta_2\, Log\,(Im\_Ag_{st}) \\
& + \beta_3\, Log\,(Im\_Mn_{st}) + \beta_4\, Log\,(Im\_Ft_{st}) + \beta_5\, Log\,(Im\_Ot_{st}) \\
& + \beta_6\, Log\,(Im\_Me_{st}) + \beta_7\, Log\,(Im\_Em_{st}) + \beta_8\, Log\,(Im\_Tr_{st}) \\
& + \beta_9\, Log\,(Im\_Om_{st}) + \beta_{10}\, Log\,(Im\_Eg_{st}) + \beta_{11}\, Log\,(Im\_Tt_{st}) \\
& + \beta_{12}\, Log\,(Im\_Bs_{st}) + \beta_{13}\, Log\,(Im\_Os_{st}) + \beta_{14}\, Log\,(GDP_{st}) \\
& + \alpha_{15}\, Population + \delta_t + \varepsilon_{st} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)
\end{aligned}
$$

In equation (1) EEE_{rt} is the concentration of emission in exporting country r in year t. Similarly, EEI_{st} in equation (2) represents the emissions in the importing country s in year t. In equations 1 and 2, coefficients α_1 and β_1 indicates the impact of trade openness on EEE and EEI respectively. Moreover, α_2 to α_{13} represents the elasticities of EEE with respect to each exporting sectors. In addition, $\beta_2$to β_{13} represents the elasticity of EEI for the trade of all importing sectors in our analysis. We suspect that there are time-specific effects, δ_t which affect all individuals in the same way.

We identify the exporting industries by Ex where r is the exporting country and we identify the importing industries by Im where s is the importing country. Grossman and Krueger (1991) and Shafik and Bandyopadhyay (1992) use the trade intensity variable, defined as the ratio of imports plus exports to GDP, to measure the openness to international trade. Trade openness is frequently used to measure the importance of international transactions relative to domestic transactions. This indicator is calculated for each country as the simple average of total trade relative to GDP. In our model α_1 and β_1 are the coefficients of trade openness which identify the impact of open trading on EEE and EEI respectively.

All industrial sectors of a country organized under a category of- 12 sectors based on the International Standard Industrial Classification and Central Product Classification (United Nations 2015a, 2015b). Agriculture (Ag), mining (Mn), food and textile (Ft), other transportable(Ot), metal products (Me), electrical and machinery (Em), transport equipment (Tr), other manufacturing (Om), electricity and gas and water (Eg), trade and transport (Tt), business services (Bs) and, other services (Os) are considered when observing sector trade effects on EEE and EEI (See table 1 for detail).

With respect to estimating regression coefficients, it is important to consider whether the response coefficients should be fixed or random. If they are assumed to be fixed, a fixed-effects panel model is appropriate for the estimation. On the other hand, if they are assumed to be random, it is appropriate to estimate equations with a generalized least squares methodology. If the Hausman test (Hausman 1978) rejects the random effects formulation in favor of fixed effects, the fixed effects panel data specification is the best model. To determine if time fixed effects are required when running a fixed effect model, we test to see if the dummies for all years are equal to 0. As they are not, a time fixed effect is necessary in our model. We estimate this by including a dummy variable for each time period.

The fixed effects models with an first order Auto Regressive (AR(1)) disturbance

EET have increased over time. Therefore, the prior level of EET(t-1) is a significant predictor of the current level of EET(t). As a result, uncorrected serial correlation is problematic in effort to predict changes in EE over time. The serial correlation in linear panel-data models biases the standard errors. So we identify serial correlation in the idiosyncratic error term in a panel- data model.

To confirm this possibility, the autocorrelation in all models was tested by using the Wooldridge test (Drukker 2003). In this test, the null hypothesis considers no autocorrelation exists in the data for a given regression model. A statistically significant F statistic confirms that alternative statistical methods are necessary to analyze the data. Our reported models herein demonstrate evidence of a first-order serial correlation. Therefore, we analyze the fixed effects models with an AR (1) disturbance. The results presented are obtained after correcting the serial correlation. Most of the variables in our model are in log terms. So the estimated coefficients are the relevant elasticities.

Other explanatory variables

The GDP of each country's economy is used as an explanatory variable because the literature on international pollution suggests that countries with more affluent economies produce higher levels of pollution per GDP. We measure economic size using estimates of the GDP, which is the total market value of the goods and services produced in a country during a given year, i.e., equal to total consumer, investment, and government spending. The GDPs are reported in U.S. dollars (billions) to facilitate cross-national comparisons. These data are derived from The World Bank's World Development Indicators Series (World Bank 2012).

Population is used to control for the influence that high population might have on the relationship between exports and emission. More populated nations tend to produce more pollution. Dietz and Rosa (1997) determined that the size of a country's population is positively related to CO_2 levels. There are also a number of time-specific factors that influence emissions. Examples of such factors include World energy prices and technological developments, etc. Following earlier studies we control for these factors by including time-specific dummy variables, as they allow us to control for factors that evolve over time and impact all countries. Table 2 includes the descriptive statistics of our explanatory variables.

Data

Calculating the EET becomes complex due to the need to enumerate the unique production systems in individual countries to a reasonable level of sectoral detail and then to link this to consumption systems through international trade data. The most common methodology for this type of analysis is a generalization of environmental input-output analysis (IOA) (Dufournaud et al. 1988) to a multiregional setting. We use the Eora multi-region input-output (MRIO) table (Lenzen et al. 2012a; Lenzen et al. 2013) as data source for some of the dependent and independent variables. The Eora MRIO table includes 187 countries and each country has between 26 and 501 sectors, for a total 15,909 sectors. This paper utilizes the EE of the disaggregated 26 to 501 sectors and aggregated them into 12 sectors. Table 1 presents the representative trading categories for every trading sectors. Industrial groupings are based on similar production processes, similar products or similar behaviors in financial markets. We directly obtain environmental emissions, gross outputs, goods and services exports and imports by commodity and trade openness from the Eora MRIO table.

This study uses multiple sources of GHG emissions and air pollutants data such as EDGAR ((European Commission Joint Research Centre (JRC))/Netherlands Environmental Assessment Agency (Environmental Assessment Agency (PBL) 2012)) and IEA energy balances (IEA & OECD 2009) as constraints and construct the direct GHG emissions and air pollutants database using constrained optimization. The MRIO analysis allows us to attribute direct environmental emissions into consuming countries and trade flows. Following Kanemoto et al. (2012), we attribute the direct GHG emissions and air pollutants D to consumers:

$$D_i^r = f_i^r x_i^r = f_i^r \left(\sum_{js} T_{ij}^{rs} + \sum_{ls} y_{il}^{rs} \right) \ \forall \ i, r$$

$$\Longleftrightarrow fx = f \ \ T1 + y1 \ \ = f \ \ Ax + y1$$

$$\Longleftrightarrow f(I-A)x = fy1$$

$$\Longleftrightarrow \mathbf{F} = \mathbf{fx} = \mathbf{f}\ \mathbf{I} - \mathbf{A}\ ^{-1}\mathbf{y1} = \mathbf{fLy1} = \sum_{rijus} f_i^r L_{ij}^{ru} y_j^{us} \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

where $\mathbf{f}$ is emission intensity with f_i^r, $\mathbf{x}$ is economic output with x_i^r, $\mathbf{T}$ and $\mathbf{y}$ are intermediate and final demands with T_{ij}^{rs} and y_{il}^{rs}, r is the exporting country, u is the last supplying country, s is the importing country, and i and j are the sectors of origin and destination. $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-\mathbf{1}}$ is the Leontief inverse equation of L_{ij}^{ru}. Equation (3) finds that the total World direct environmental emissions are the same as the total World indirect emissions because a country's EEE are another countries' EEI and vice versa. We use the embodied greenhouse gas emissions and air pollutants in exports and imports section by decomposing equation (4):

$$\underbrace{F_j^s}_{production} = \sum_r f_i^r \left[\underbrace{\sum_{iu} L_{ij}^{ru} y_j^{us}}_{consumption} - \underbrace{\sum_{iu \neq s} L_{ij}^{ru} y_j^{us}}_{EEI} + \underbrace{\sum_{is \neq u} L_{ij}^{rs} y_j^{su}}_{EEE} \right] \ldots\ldots\ldots\ldots\ldots\ldots. (4)$$

The GDP data are the sum of the gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. GDP is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. The data are in current U.S. dollars. The data on population simply refer to the total population in millions counting all residents regardless of legal status or citizenship except for refugees not permanently settled in the country of asylum (who are generally considered part of the population of their country of origin).

Results and discussion

Our analysis shows that a significant share of global EE arise from the production of internationally traded goods and services. The results of the regression are displayed in Table 3 and 4. We investigate the impact of trade openness and sectoral trade on EET. We consider the emission of three GHG: carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) in our model and focus on the EE of these pollutants by considering the trade of 12 industrial sectors. We also consider five air pollutants: carbon monoxide (CO), non-methane volatile organic compounds (NMVOC), nitrogen oxides (NO_X), particulate matter (PM_{10}) and sulphur dioxide (SO_2) in our analysis and identify how trade openness and sectors trade impact EET.

Our empirical results suggest that trade openness contributes to the EE of GHG and air pollutants. The coefficient trade openness variable in the regression table 3 and 4 are statistically significant for all GHG and air pollutants. Figure 1 indicates the trade openness effects on EEE and EEI. From 1990 to 2011, due to global exports, EE of CO_2 increased by 10.5%, CH_4 increased by 14.7% and N_2O increased by 23.6%, (Fig. 1). With respect to five air pollutants, we notice significant increase in EEE due to trade openness. Specifically, CO increased by 17.8% and NMVOC increased by16.5%. Figure 2 presents the country-specific trade openness condition. When the trade openness score is greater than one, trade volume of the economy exceeds the GDP. In figure 2, some European countries and a few Asian and African countries exhibit high trade openness score [(export + import)/ GDP >1].

Less input relative to output in the agricultural sector is particularly important for explaining the emissions of methane (Bruvoll and Larsen 2004). In recent years, many empirical studies have focused on the estimations of CH_4 emissions from agricultural activities (Yamaji et al. 2003; Guo and Zhou 2007; Huang et al. 2006). Some literatures have also focused on the impact of mining on CH_4 and N_2O emission (Bibler et al. 1998; YUAN et al. 2006; Yang 2009). We also note that the agriculture sector coefficient is positively correlated with embodied CH_4 emission. For example, in our analysis, a 1% increase in agriculture product exports can increase embodied CH_4 emissions by 0.04%. In addition, a 1% increase of mining product exports causes a 0.04% increase in embodied CH_4 emissions and a 0.06% increase in embodied N_2O emissions.

Eyring et al. (2010) identified the growing contribution to the total emissions from the transportation sector. We find that the trade and transport sector have significant impact on the EEE of GHG and air pollutants. According to our findings, a 1% increase in the trade and transport services increases EEE of CO_2 by 0.44%, NOx by 0.24%, and SO_2 by 0.35%. NMVOC is a group of compounds, the composition of which depends on the source. A 1% increase in the mining, metal, electrical and electricity sectors increases by 0.05%, 0.08%, 0.06% and 0.06% the EEE of NMVOC respectively.

Sánchez-Chóliz and Duarte (2004) found that exports of embodied CO_2 emissions are mainly concentrated in the basic sectors of the Spanish economy – mining and energy, non-metallic industries, chemicals, and metals. We analyze the EEE for 187 countries and find mining, metal, electricity sectors affet on CO_2 emission. A 1% increase in mining, metal, electricity sectors export increases EEE of CO_2 by 0.1%, 0.05%, 0.03% respectively. Wyckoff and Roop (1994) find that about 13% of the CO_2 emissions of six major OECD countries were embodied in their manufactured imports. But in our analysis, the global manufacturing trade have no significant impacting on EEI of CO_2. Import of a 1% mining product increse EEI of CO_2 by a 0.14%.

We found that mining sector trading is closely related with EEE of NOx, PM_{10} and SO_2. A 1% increase in mining sectors increases exports by 0.04%, 0.06% and 0.05% in embodied NOx, PM_{10} and SO_2 emission, respectively. The electricity sector is also a contributor of EEE of these air pollutants. A 1% additional export of electricity will cause a 0.07% increase in NOx, a 0.06% increase in PM_{10} and a 0.55% increase in SO_2 emissions. The metal sector is another important sector whose impact on EEE of air pollutants is always positive. In our analysis, a 1% increase in meatal sector exports increased the EEE of NOx, PM_{10} and SO_2 by 0.06%, 0.09% and 0.08%, respectively.

Emissions of particulates (PM_{10}) are targeted for reduction by the World Health Organization (WHO 2000) due to their adverse effects on human health and the environment. We determined that a 1% increase in trade and transport, electricity, metal, mining and electrical sectors increases by 0.18%, 0.06%, 0.10%, 0.06% and 0.06% the embodied PM_{10} emission by export, respectively. A 1% increases in electrical import results 0.2% increase in the embodied PM_{10} emissions.

Pollution-intensive production increases a country's GDP as well as its emissions. We present the GDP impact on EEE and EEI in figure 3 and the global GDP condition in figure 4. According to our findings, the GDP impact on EEE and EEI is always significant. Due to symmetry, the global EEI are the same as the global EEE. Thus, our findings suggest that the GDP increases EEE and reduce EEI. For instance, in figure 3, in the case of CO_2, we notice that 1% increase in the national GDP results in an increase of 0.3% in EEE. Other GHG and air pollutants are also significantly affected by the GDP. Socio-demographic drivers like population impact on EEE of CO, NMVOC and SO_2 are statistically significant. We note that a million increase of population will increase EEE of CO, NMVOC and SO2 by 0.001%, 0.002% and 0.002%, respectively.

Conclusion and policy implications

The analysis reported above supports the hypothesis that there is a positive relationship between trade and EE across a sample of 187 nations during the years 1990 through 2011. Industry-specific export and import analysis revealed that GHG and air pollutants are strongly impacted by global trade. In short, the greater the increase in the exporting of mining products, metal products, electrical, electricity, trade and transport, and other manufacturing products, the greater the increase in

EEE. This analysis clearly indicate that the import of electrical products impacts EEI.

Analysis of EEE is important when making policy decisions on at least two levels, the local and regional scale pollution level, while the global policy effectiveness concerns impact pollution levels on a global scale. Local scale pollutants such as SO_2 and NOx, which are emitted in one country to produce goods for export to another country, usually affect only people in the exporting country or surrounding area. A large body of literature has examined such equity concerns and issues, i.e., whether the positive impact of increased trade outweigh potential negative environmental impacts (e.g., Muradian et al. 2002; Giljum and Eisenmenger 2004).

There are few studies that examine the impact of trade openness on global EET by considering different air pollutants and GHG. The results of our study indicate that the trade openness and GDP are important factors in shaping EET and therefore, they are important when creating environment policy. Policy implications can be drawn from this paper. First, trade openness can significantly increase EET at a global level. Second, the emission reduction policy should focus on individual trading sectors. UNFCCC members submitted their future GHG emissions reduction targets for COP21. However, the targets do not take into account the future economic, environmental, and demographic variables, such as EET, trade openness, and population, even though our study finds that these variables actually determine emission levels.

The most suitable model for usage in EET analysis depends on the research question and the purpose of the particular application. Our global analysis estimates the overall contribution of the trading sectors on EET. Research which seeks to estimate country-specific EET, however, need to consider regional technology.

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Figure Captions

Figure 1: Trade openness impact on embodied emissions in international trade (EET)

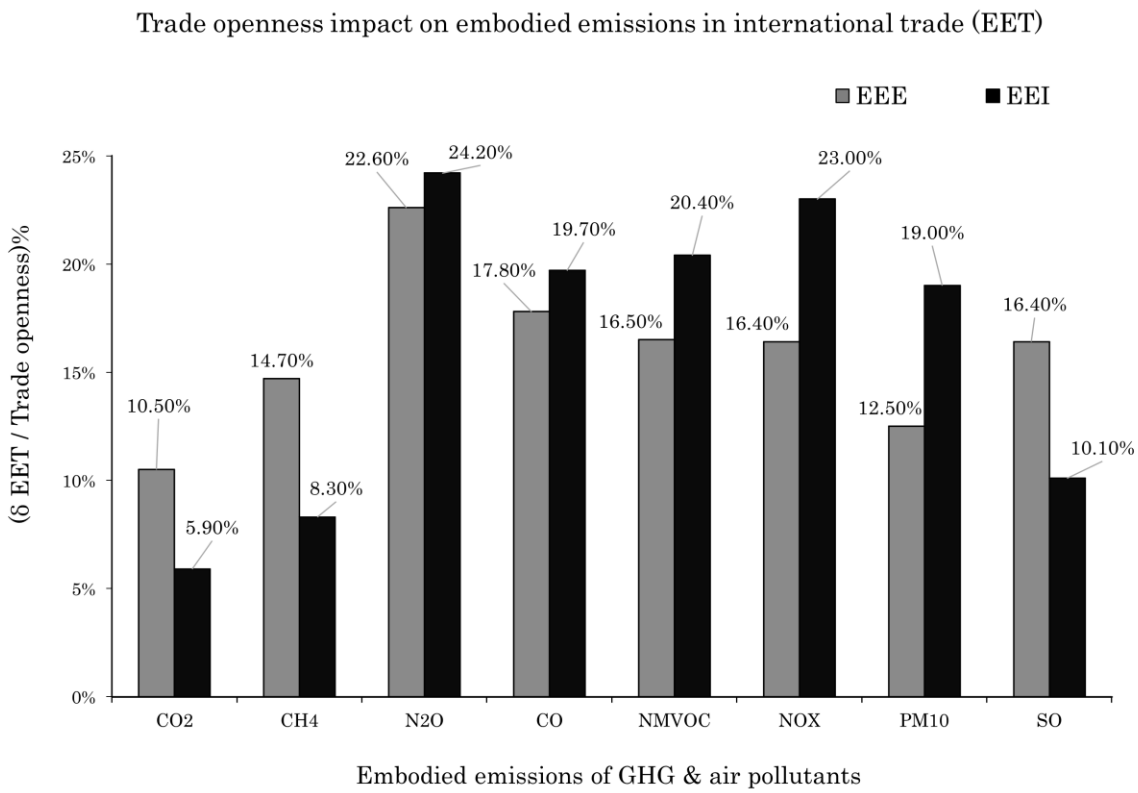

Figure 2: Country trade openness score (trade/GDP)

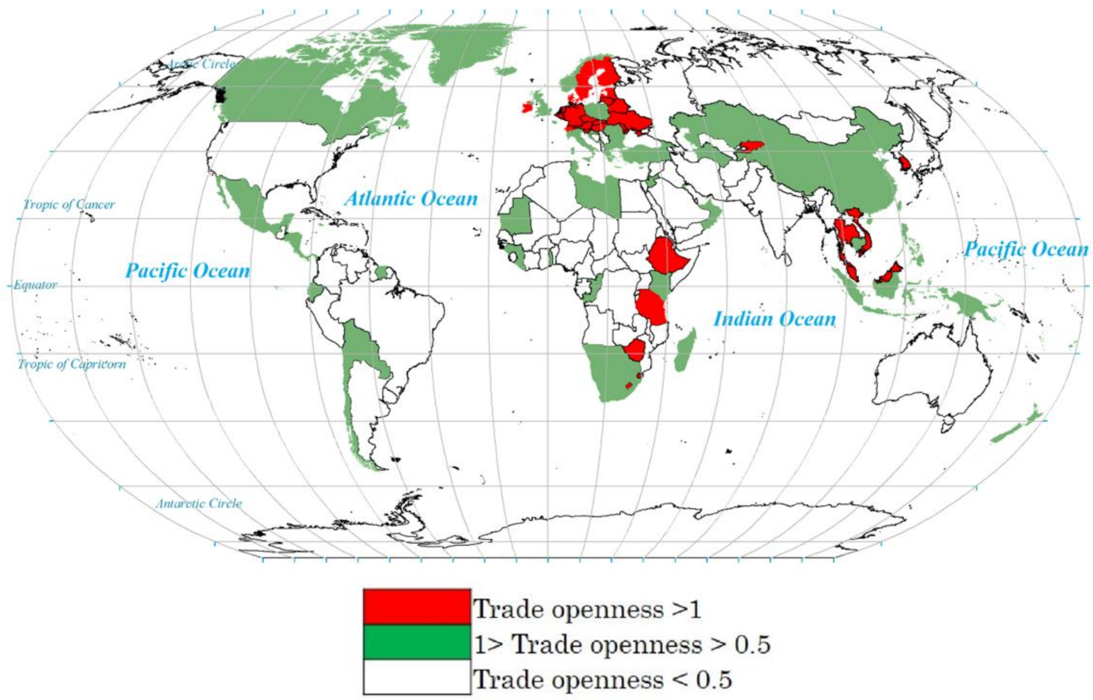

Figure 3: Impact of GDP on embodied emissions in international trade (EET)

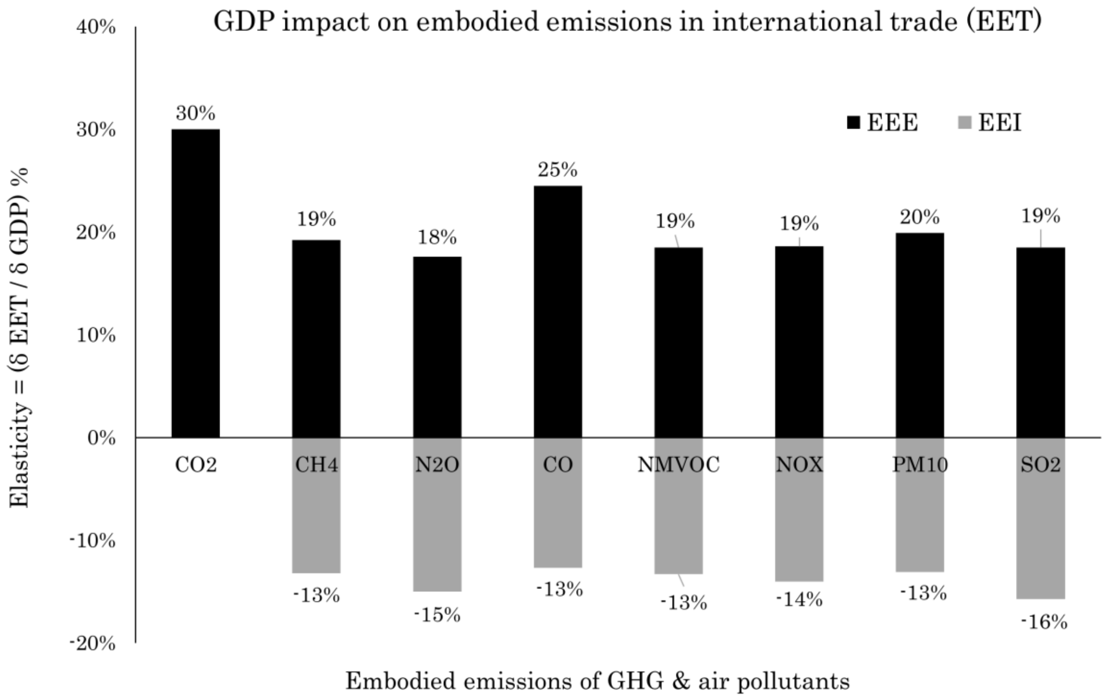

Figure 4: Country GDP condition (source: World Bank and OECD national account data)

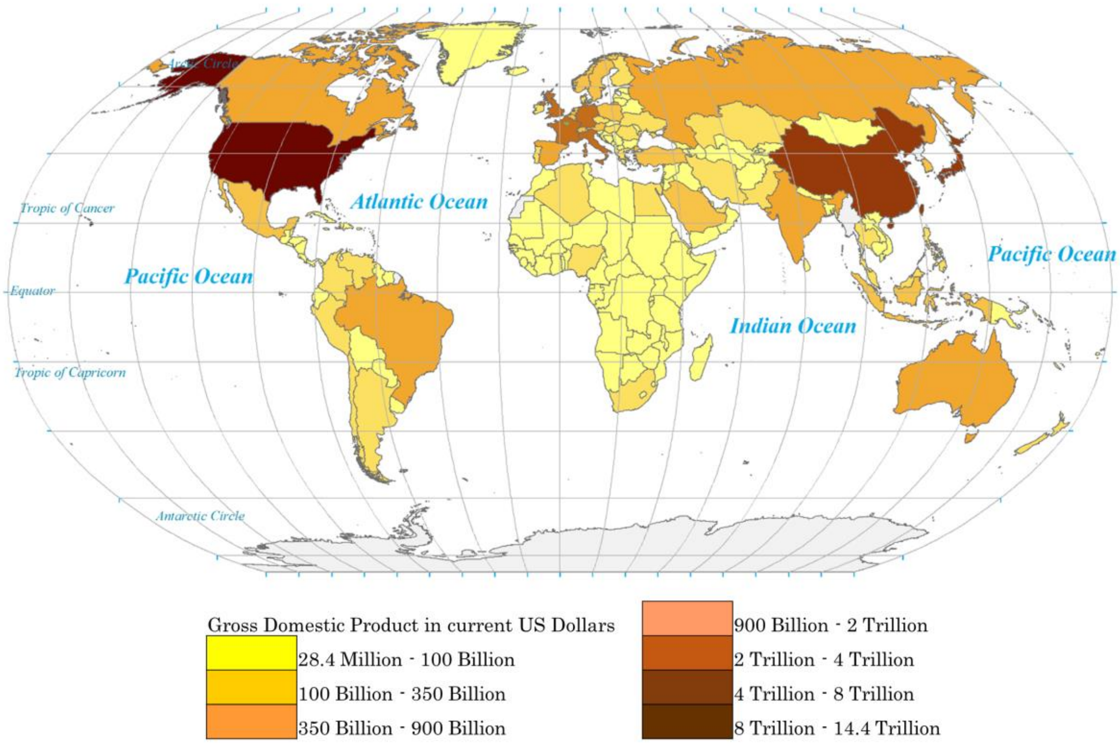

Table 1: Trade sectors

Sectors	Industries
S1. Agriculture	Agriculture; Fishing
S2. Mining	Mining and Quarrying
S3. Food & Textile	Food & Beverages; Textiles and Wearing Apparel
S4. Other transportable	Wood and Paper; Petroleum, Chemical and Non-Metallic Mineral Products
S5. Other Manufacturing	Other Manufacturing; Recycling
S6. Metal products	Metal Products
S7. Electrical & Machin	Electrical and Machinery
S8. Transport Equipment	Transport Equipment
S9. Elec & gas & water	Electricity, Gas and Water
S10. Trade and transport	Wholesale Trade; Retail Trade; Transport; Post and Telecommunications
S11. Business services	Financial Intermediation and Business Activities
S12. Other services	Construction; Maintenance and Repair; Hotels and Restaurants; Public Administration; Education, Health and Other Services; Private Households; Others

Table 2: Descriptive statistics of explanatory variables in EEE model

Variable	*Obs.*	*Mean*	*Std. D*	*Min*	*Max*
Trade openness (trade/GDP)	4092	0.601815	0.663078	0.012674	9.1061
Agriculture_Export	4092	363755.4	1036009	181.7601	1.59E+07
Mining_ Export	4092	21261.8	71536.78	112.8	1100000
Food & textile_ Export	4092	3020719	1.04E+07	228.343	2.31E+08
Other transportable_ Export	4092	1449583	4647664	225.89	6.29E+07
Metal products_ Export	4092	232531.2	877865.4	112.8	1.70E+07
Electrical & machine_ Export	4092	4885766	1.77E+07	114.112	2.60E+08
Transport equipment_ Export	4092	2772212	1.22E+07	88.5644	2.00E+08
Other manufacture_ Export	4092	841748.8	3415284	210.1525	7.85E+07
Elec & gas & water_ Export	4092	15479.64	66732.8	112.8	1000000
Trade & transport_ Export	4092	1092521	4149422	457.021	7.18E+07
Business services_ Export	4092	478455.4	2270999	112.8	5.30E+07
Other services_ Export	4092	840338.6	2535966	798.823	3.66E+07
GDP (current US dollar)	4092	6.82E+08	3.46E+09	81843.3	6.40E+10
Population (million)	3935	33.46895	125.7992	0.024135	1300

Note: The unit of sectoral export is 1000 USD.

Descriptive statistics of the explanatory variables in EEI model is approximately equal for mean and standard deviation.

Table 3: Regression result for EEE: FE model with AR (1) errors [a]

Variables	GHG			Air Pollutants						
	Log (CO_2)	Log (CH_4)	Log (N_2O)	Log (CO)[c]	Log(NMVOC)	Log (NOx)	Log (NOx)[c]	Log (PM_{10})	Log (SO_2)	Log (SO_2)[c]
Trade openness	0.105***	0.147***	0.226***	0.178***	0.165***	0.164***	0.159***	0.125***	0.164***	0.166***
	(0.0309)	(0.0242)	(0.0206)	(0.0204)	(0.0248)	(0.0257)	(0.0203)	(0.0294)	(0.0265)	(0.0208)
Log (Agriculture)	-0.0320	0.0411**	0.00429	-0.0184	-0.00145	-0.00637	-0.0230	-0.0329	-0.0207	-0.0290*
	(0.0246)	(0.0195)	(0.0168)	(0.0155)	(0.0194)	(0.0202)	(0.0152)	(0.0229)	(0.0207)	(0.0156)
Log (Mining)	0.0928***	0.0399***	0.0614***	0.0485***	0.0486***	0.0407***	0.0409***	0.0603***	0.0501***	0.0432***
	(0.0189)	(0.0150)	(0.0130)	(0.0131)	(0.0149)	(0.0156)	(0.0129)	(0.0175)	(0.0159)	(0.0132)
Log (Food & text)	-0.113***	-0.0354**	-0.0878***	-0.0736***	-0.0532***	-0.0646***	-0.0778***	-0.0560**	-0.0804***	-0.0827***
	(0.0229)	(0.0180)	(0.0155)	(0.0153)	(0.0184)	(0.0191)	(0.0151)	(0.0219)	(0.0197)	(0.0155)
Log (Other trans)	-0.00784	-0.00451	0.0133	0.0226	-0.0106	-0.00192	0.0252	-0.0413*	-0.0205	0.0159
	(0.0252)	(0.0196)	(0.0167)	(0.0167)	(0.0206)	(0.0212)	(0.0168)	(0.0250)	(0.0221)	(0.0173)
Log (Metal)	0.0487*	0.0286	0.0422**	0.0615***	0.0763***	0.0622***	0.0645***	0.0969***	0.0850***	0.0781***
	(0.0256)	(0.0200)	(0.0171)	(0.0179)	(0.0209)	(0.0215)	(0.0180)	(0.0254)	(0.0224)	(0.0186)
Log (Electrical)	0.0885***	0.0370**	0.0569***	0.0497***	0.0570***	0.0590***	0.0556***	0.0574***	0.0473**	0.0444***
	(0.0210)	(0.0163)	(0.0138)	(0.0150)	(0.0176)	(0.0180)	(0.0153)	(0.0217)	(0.0189)	(0.0159)
Log (Transport equipment)	-0.00729	0.0146	0.000127	-0.00895	-0.00150	0.00616	0.00332	-0.0110	-0.00226	-0.00495
	(0.0145)	(0.0112)	(0.00950)	(0.0103)	(0.0121)	(0.0124)	(0.0105)	(0.0150)	(0.0130)	(0.0109)

Log (Other manufacturing)	-0.0182	0.0250	-0.0215	0.0373**	-0.0130	-0.0233	0.0193	0.00514	-0.0279	0.0266
	(0.0250)	(0.0194)	(0.0165)	(0.0165)	(0.0206)	(0.0212)	(0.0166)	(0.0250)	(0.0221)	(0.0171)
Log (Electricity)	0.0287*	0.0502***	0.0474***	0.0529***	0.0608***	0.0644***	0.0749***	0.0607***	0.0547***	0.0560***
	(0.0161)	(0.0128)	(0.0111)	(0.0117)	(0.0127)	(0.0133)	(0.0117)	(0.0148)	(0.0135)	(0.0120)
Log (Trade & transport)	0.437***	0.196***	0.337***	0.366***	0.119**	0.242***	0.336***	0.183***	0.347***	0.435***
	(0.0740)	(0.0587)	(0.0509)	(0.0496)	(0.0582)	(0.0608)	(0.0486)	(0.0683)	(0.0621)	(0.0499)
Log (Business)	-0.0500***	-0.0311***	-0.0273***	0.0255***	-0.0170*	-0.0182**	0.00949	-0.0271**	-0.0116	0.00820
	(0.0111)	(0.00873)	(0.00753)	(0.00829)	(0.00890)	(0.00922)	(0.00834)	(0.0107)	(0.00951)	(0.00861)
Log (Other services)	-0.398***	-0.311***	-0.307***	-0.283***	-0.163***	-0.257***	-0.279***	-0.172***	-0.299***	-0.318***
	(0.0696)	(0.0553)	(0.0480)	(0.0469)	(0.0551)	(0.0575)	(0.0461)	(0.0647)	(0.0588)	(0.0472)
Log (GDP)	0.300***	0.192***	0.176***	0.245***	0.185***	0.186***	0.259***	0.199***	0.185***	0.261***
	(0.0161)	(0.0123)	(0.0103)	(0.0117)	(0.0133)	(0.0135)	(0.0122)	(0.0168)	(0.0143)	(0.0127)
Population_ million	0.0005	-0.0005	-0.0002	0.0013***	0.0018***	0.0005	0.0009***	0.0010	0.0016***	0.0010***
	(0.0009)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0002)	(0.0006)	(0.0006)	(0.0002)
Constant	0.641***	0.151	-1.721***	-3.559***	-0.496***	-0.549***	-3.498***	-1.108***	-0.640***	-3.770***
	(0.215)	(0.161)	(0.134)	(0.201)	(0.0861)	(0.0793)	(0.198)	(0.139)	(0.0957)	(0.205)
Observations	3,756	3,756	3,756	3,934	3,754	3,754	3,933	3,755	3,755	3,934
Country	179	179	179	179	179	179	179	179	179	179
R squared	0.3538	0.5181	0.3938	0.8868	0.9051	0.8597	0.8918	0.8680	0.8296	0.8881

Country FE	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hausman test [d]	6.18**	303.27***	323.32***	0.03	127.57***			1150.81***		
Wooldridge test [e]	198.874***	198.219***	100.949***	52.980***	11.473***	25.096***	25.096***	3.924**	4.247**	4.247**

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

a All estimates are estimates from the FE model with AR (1) disturbances, unless otherwise indicated.

b Indicates the estimates are from the FE model only.

c Indicates the estimates are from the RE model with AR (1) disturbances.

d The Hausman test provides a $\chi^2(.)$ statistic. If the p value is <β (the significance level), we strongly reject the null hypothesis that β_i are uncorrelated with the regressors. This justifies the usage of the fixed-effects model.

e The null hypothesis of the Wooldridge test that no autocorrelation exists in the data for a given regression model. If the p value is <α (the significance level), we strongly reject the null hypothesis. This justifies the evidence of first-order serial correlation in the data.

Table 4: Regression result for EEI: FE model with AR (1) errors [a]

Variables	GHG			Air Pollutants				
	Log (CO_2)	Log (CH_4)	Log (N_2O)	Log (CO)	Log (NMVOC)	Log (NOx)	Log (PM_{10})	Log (SO_2)[b]
Trade openness	0.0587**	0.0825**	0.242***	0.197***	0.204***	0.230***	0.190***	0.101***
	(0.0251)	(0.0402)	(0.0373)	(0.0285)	(0.0220)	(0.0250)	(0.0264)	(0.0150)
Log (Agriculture)	0.0784	-0.0767	-0.0848	-0.0720	-0.0634	-0.0440	-0.106	-0.161***
	(0.0637)	(0.102)	(0.0950)	(0.0725)	(0.0560)	(0.0635)	(0.0671)	(0.0456)
Log (Mining)	0.136***	0.00807	-0.0882*	-0.0467	-0.0475	-0.0477	-0.0267	-0.0218
	(0.0357)	(0.0553)	(0.0509)	(0.0400)	(0.0306)	(0.0348)	(0.0368)	(0.0200)
Log (Food & textile)	0.0103	-0.0293	-0.198*	0.0382	-0.0336	-0.0153	0.00142	0.106**
	(0.0792)	(0.121)	(0.112)	(0.0878)	(0.0671)	(0.0764)	(0.0806)	(0.0471)
Log (Other transportable)	-0.0181	-0.129	0.212*	0.0247	0.0807	0.0642	0.133	0.423***
	(0.0797)	(0.127)	(0.119)	(0.0907)	(0.0702)	(0.0797)	(0.0842)	(0.0565)
Log (Metal)	0.0881	0.0430	-0.0970	-0.115	-0.121**	-0.0999	-0.0613	-0.00292
	(0.0703)	(0.111)	(0.102)	(0.0791)	(0.0608)	(0.0691)	(0.0730)	(0.0447)
Log (Electrical)	-0.0993	0.203*	0.167	0.275***	0.185***	0.188**	0.194**	0.0601
	(0.0764)	(0.122)	(0.111)	(0.0860)	(0.0660)	(0.0751)	(0.0793)	(0.0487)
Log (Transport equipment)	0.0295	0.0402	0.0319	-0.0926*	-0.0272	-0.0168	-0.0208	-0.0495
	(0.0474)	(0.0735)	(0.0684)	(0.0532)	(0.0408)	(0.0465)	(0.0490)	(0.0316)
Log (Other manufacturing)	-0.158**	-0.0194	-0.0281	-0.0555	-0.0348	-0.0699	-0.122*	-0.117***
	(0.0731)	(0.110)	(0.100)	(0.0806)	(0.0612)	(0.0698)	(0.0736)	(0.0384)

Log (Electricity)	0.0348	-0.0249	-0.0284	0.0265	0.0218	0.00963	0.00611	-0.0460***
	(0.0268)	(0.0422)	(0.0391)	(0.0302)	(0.0232)	(0.0264)	(0.0279)	(0.0171)
Log (Trade & transport)	-0.0491	-0.125	-0.0825	-0.122	-0.139**	-0.0892	-0.217***	-0.352***
	(0.0735)	(0.115)	(0.108)	(0.0821)	(0.0633)	(0.0719)	(0.0759)	(0.0529)
Log (Business)	-0.0388	0.0527	0.0791	-0.0642	-0.0434	-0.0267	0.0282	-0.0481
	(0.0509)	(0.0811)	(0.0758)	(0.0578)	(0.0447)	(0.0507)	(0.0536)	(0.0379)
Log (Other services)	0.0372	-0.122	-0.0235	0.0237	0.0608	-0.0284	0.0213	0.120**
	(0.0741)	(0.118)	(0.109)	(0.0832)	(0.0642)	(0.0730)	(0.0771)	(0.0548)
Log (GDP)	-0.0151	-0.132***	-0.150***	-0.127***	-0.133***	-0.140***	-0.131***	-0.157***
	(0.0123)	(0.0207)	(0.0196)	(0.0142)	(0.0111)	(0.0125)	(0.0133)	(0.0113)
Population _million	-0.0004	-0.00003	0.0006	-0.0005	-0.0005	-0.0005	0.0002	0.0030***
	(0.0008)	(0.0012)	(0.0010)	(0.0009)	(0.0007)	(0.0007)	(0.0008)	(0.0004)
Constant	-4.026***	0.407**	-0.962***	-3.895***	-3.807***	-3.870***	-3.702***	2.972***
	(0.157)	(0.195)	(0.168)	(0.120)	(0.0911)	(0.103)	(0.109)	(0.0853)
Observations	3,663	3,625	3,652	3,644	3,643	3,643	3,643	3,817
Number of country	176	173	175	174	174	174	174	174
R squared	0.2263	0.1004	0.1063	0.1530	0.2350	0.2036	0.1769	0.1008
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hausman test [d]	212.32***	108.28***	161.12***	323.99***	647.79***	487.20***	433.91***	2526.44***
Wooldridge test [e]	173.211***	31.608***	14.736***	29.219***	36.323***	43.991***	15.698***	0.386

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[a] All estimates are estimates from the FE model with AR (1) disturbances, unless otherwise indicated.

[b] Indicates the estimates are from the FE model only.

[c] Indicates the estimates are from the RE model with AR (1) disturbances.

[d] The Hausman test provides a $\chi^2(.)$ statistic. If the p value is $< \beta$ (the significance level), we strongly reject the null hypothesis that β_i are uncorrelated with the regressors. This justifies the usage of the fixed-effects model.

[e] The null hypothesis of the Wooldridge test that no autocorrelation exists in the data for a given regression model. If the p value is $< \alpha$ (the significance level), we strongly reject the null hypothesis. This justifies the evidence of first-order serial correlation in the data.